Application Of Sparrow Search Algorithm in Cold Chain Low Carbonization Logistics

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Abstract. Driven by consumer upgrades and national policies, the cold chain logistics industry has experienced rapid development, accompanied by increased expenditure of energy and carbon emissions. To achieve energy savings, emission reductions, and overall cost reduction in the cold chain logistics industry, this article establishes an optimization model for optimizing transportation routes, taking into account carbon emission costs, refrigeration costs, and time penalty costs. The objective is to comprehensively consider reducing refrigeration costs and time penalty costs throughout the entire phase of cold chain logistics, aiming to minimize the total cost for logistics companies during actual delivery processes. The improved Sparrow Search Algorithm (SSA) is employed to solve the optimization problem. The results of the case study analysis validate the applicability and superiority of the improved SSA for route optimization problems, as it demonstrates fast convergence speed and strong search capabilities.

Keywords: Cold Chain Logistics, Carbon Cost, Improved Sparrow Search Algorithm, Path Optimization.

1. Introduction

In recent years, China's cold chain product market has grown rapidly, but there is no cold chain distribution system that can better adapt to market changes [1].

Currently, cold chain logistics optimization has gained attention from both domestic and international scholars. Liang et al. [2] developed an optimization model for cold chain logistics distribution, focusing on minimizing costs and enhancing the Particle Swarm Optimization (PSO) algorithm for logistics distribution. Wang et al. [3] addressed the Vehicle Routing Problem (VRP) in cold chain logistics with time window constraints and China's carbon tax, proposing a Cyclic Evolutionary Genetic Algorithm (CEGA) to minimize distribution costs. Qiao [4] determines a cold chain logistics distribution route model based on time, temperature, and damage costs to minimize total costs. Zhang et al. [5] integrated cold chain logistics into the cost economy, using RNA computing and ant colony algorithms to reduce total logistics costs and carbon emissions, and built a route optimization model that included carbon emissions costs. Huang et al. [6] developed a cold chain management model for agricultural products, which improved circulation efficiency and reduced losses between nodes. According to the cold chain logistics network structure, Lu et al. [7] optimizes the railway cold chain logistics network between the two major urban agglomerations in China, and uses A-Saga to determine the optimal transportation scheme. Ba et al. [8] introduced an emergent cold chain logistics distribution model with a time window to minimize costs and delivery time in uncertain demand scenarios. Xiong [9] presented a cold chain logistics distribution route optimization scheme based on IACO, demonstrating improved convergence speed and reduced transportation distance and distribution time. Shu et al. [10] formulated LIRP under a satellite storage model to minimize total costs in a cold chain logistics system for a supermarket chain. Chen [11] improves the efficiency and reduces the cost of cold chain logistics for fresh products, proposing an improved genetic algorithm to optimize location selection in green cold chain logistics. Shi et al. [12] combined Dijkstra and NSGA-II algorithms to propose an intelligent cold chain logistics green scheduling system framework that supports resource integration and unloading.

The above literature seldom considers the lowest total cost, the reduction of carbon emissions, and the time penalty cost, and the research on relevant problems mainly uses a genetic algorithm or ant colony algorithm, the convergence frequency is slowed down, and it is easier for it to fall into local optimal solutions. At present, there is no research on multi-objective optimization with carbon emission as the main optimization direction of the SSA. Therefore, based on the theory of SSA, this paper puts forward a new optimization model of cold chain logistics with cold storage cost, time penalty cost and carbon emission cost as the main cost factors and carbon emission as the main optimization direction.

2. Optimization model construction

In this paper, cold storage cost, time penalty and carbon emission are taken as the key cost factors when constructing the mathematical model of optimal scheduling. Combined with the general trend of China's green logistics, carbon emission is the main optimization direction. The structure of each cost analysis is as follows:

2.1. Refrigeration cost

The cost of refrigeration is proportional to the inventory, and the power consumption is also proportional, that is, the more inventory, the greater the power consumption, the higher the cost of refrigeration. The cost of refrigeration in a cold chain distribution center is shown below. Where F represents the cooling cost of the cold chain distribution center.

$$F_1 = \frac{Q^*}{2} ht_0 + w_1(kVe_c t_0 + 0.406(T_1 + T_0)Q^*) \tag{1}$$

In this formula, the average inventory cost of a cold chain distribution center is represented: the unit is *yuan* /(*t*· *d*); 30 represents the average daily temperature of a city in summer (°C).

2.2. Time penalty cost

In many versions of the vehicle routing problem, the time window adds a delivery time constraint to the service customer. That is, each customer's service should begin within a given time window. If the vehicle arrives at the service point before the service starts, it must wait, and during the waiting period, the vehicle cannot be served. On the contrary, if the vehicle arrival time violates its constraints, there will be a time delay.

Here we formulaic it as the delay time cost caused by the logistics vehicle not arriving in accordance with the constraint time, and the time penalty cost formula is as follows:

$$F_2 = p\sum_{v=1}^{V}\sum_{i,j=1}^{n}\max(et_j^v - t_j^v, 0) \tag{2}$$

In this formula: F_2 represents the time penalty cost.

2.3. Carbon emission cost

In our model, we creatively consider the cost of carbon emission, because carbon emission is a link that must be taken into account in cold chain logistics, and the flow chart of cold chain logistics is shown in Figure 1.

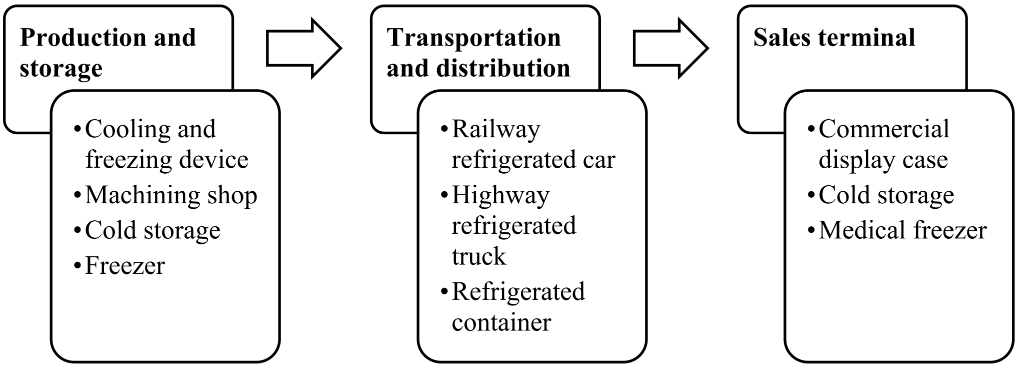

Figure 1. Flowchart of cold chain logistics

Cold chain equipment is the core component of cold chain logistics. In all links of the cold chain supply chain, it is observed that carbon emissions are mainly generated in cold storage, freezers, refrigerated trucks, including late warehouse storage. Based on these connections and existing literature, the calculation method of carbon emissions in this paper is as follows:

$$F_3=\sum_{l\in L}\sum_{k\in K}\sum_{i=T_1}\sum_{j\in N}x_{ij}^{kl}\cdot\omega e_0 d_{ij}^{kl}(a^{kl}y_{ij}^{kl}+b^{kl})+\sum_{l\in L}\sum_{k\in K}\sum_{i=T_1}\sum_{j\in N}\omega e_1 h_i y_{ij}^{kl}+\sum_{l\in L}\sum_{k\in K}\sum_{i\in N}\sum_{j=T_2}\omega e_1 h_j y_{ij}^{kl} \tag{3}$$

2.4. Basic formula setting

In the actual distribution process, the goal of enterprises is to minimize the total cost, and this paper adds the weight of carbon emission cost on this basis. The cold chain logistics optimization model is built as follows:

$$\begin{aligned}\min C=&\frac{Q^*}{2}ht_0+w_1(kVe_ct_0+0.406(T_1-T_0)Q^*)+\\&P\sum_{v=1}^{V}\sum_{iJ=1}^{n}\max(et_j^v-t_j^v,0)+\sum_{l\in L}\sum_{k\in K}\sum_{i=T_1}\sum_{j\in N}x_{ij}^{kl}\cdot\omega e_0 d_{ij}^{kl}(a^{kl}y_{ij}^{kl}+b^{kl})+\\&\sum_{l\in L}\sum_{k\in K}\sum_{i=T_1}\sum_{j\in N}\omega e_1 h_i y_{ij}^{kl}+\sum_{l\in L}\sum_{k\in K}\sum_{i\in N}\sum_{j=T_2}\omega e_1 h_j y_{ij}^{kl}\end{aligned} \tag{4}$$

$$Q^*\le N_{\max} \tag{5}$$

$$\sum_{v=1}^{V}\sum_{i,j=0}^{n}q_i x_{ij}^v=Q^* \tag{6}$$

$$\sum_{i=1}^{n}y_i^v q_i\le Q \tag{7}$$

$$\sum_{v=1}^{V}\sum_{i,j=0}^{n}x_{i,j}^v<V,\ j=0 \tag{8}$$

$$\sum_{i=1}^{n}x_{i,j}^v=\sum_{i=1}^{n}x_{j,i}^v,\ v=\{1,2,\cdots,V) \tag{9}$$

3. Optimization of Sparrow search algorithm model

SSA is a swarm intelligent optimization algorithm. The solution of each optimization problem is similar to a sparrow in the search space, each sparrow has its energy, and the energy value of each sparrow is represented by a functional adaptation value. Among them, sparrows are divided into discoverers and participants. To better adapt to the conditions of this paper, we carry out the following optimization and improvement.

3.1. Model assumption

1. Do not consider the interference of weather conditions in the logistics distribution process.
2. It is assumed that transport vehicles such as refrigerated trucks and trucks arrive at the distribution place at a constant speed, without considering the impact of accidents such as traffic jams on carbon emissions.
3. Assume that suppliers and customers are fixed, and the logistics distribution path is also fixed, and there will be no temporary changes.
4. The number of refrigerated trucks is fixed to meet the needs of the supply chain without redundancy and avoid the impact of additional carbon emissions.
5. A refrigerated delivery vehicle can serve multiple customers at the same time, but each customer can only be delivered by one vehicle.

3.2. The specific steps of the algorithm

1. Initialize SSA parameters. Initialize the parameter values and variables of the SSA: the maximum number of iterations G, the total number of sparrows N, the number of sparrow searchers PD, and the number of participants M-PD.
2. Obtain the current optimal sparrow position and the global optimal sparrow position, and randomly set the alert position.
3. Calculate the initial fitness value. The higher the fitness value of the sparrow in the algorithm, the higher the energy reserve; The smaller the fitness function value, the more accurate the training and the better the prediction accuracy of the model. The current fitness value and the global optimal sparrow position were used to find the best individual, the worst individual and the optimal sparrow position.
4. Calculate the warning value. In the sparrow population, the fitter finder will give priority to finding food and provide foraging directions for the sparrow population. The sparrows found had a larger feeding range than the participants.
5. Sparrow position with the best-fit value.
6. Check whether the algorithm is complete. If the algorithm is complete, go to Step 2. The specific calculation process is shown in Figure 2.

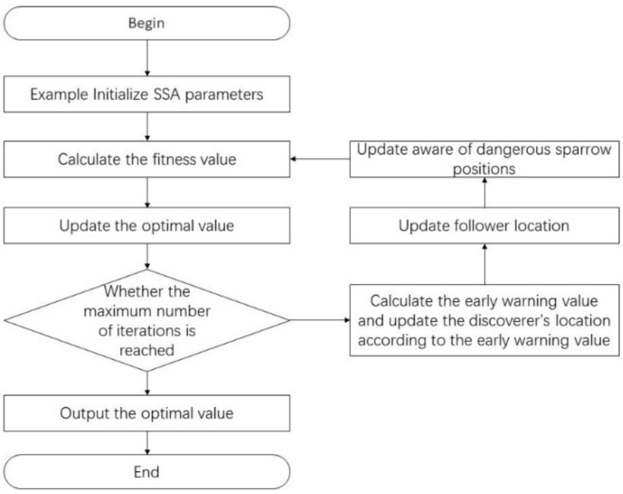

Figure 2. SSA model building flow chart

4. Case study

In order to prove that SSA is more efficient than genetic algorithm and particle swarm optimization in path optimization for low-carbon optimization, we can design the following control experiments:

4.1. Experimental objectives

The efficiency of SSA, genetic algorithm and particle swarm optimization in low-carbon path optimization is compared.

4.2. Experimental procedure:

1. Methodology

The graph was defined as a 20x20 grid, with 400 nodes. The start and end points were set at the upper left and lower right corners respectively. Each node was assigned a random carbon emission value between 0 and 10.

The parameters for the SSA included a population size of 20, a maximum iteration count of 100, and a migration probability of 0.5. Similarly, the Genetic Algorithm had a population size and maximum iteration count of 20 and 100 respectively, with a crossover probability of 0.8 and mutation probability of 0.1. The Particle Swarm Optimization used 20 particles, maximum iterations of 100, an inertia weight of 0.5, and individual and social learning factors of 1.0.

2. Experiment Procedure

The procedure involved generating a random chart with carbon emissions assigned to each node. The three algorithms were used to find the shortest path from start to end, recording the total carbon emission and execution time. This process was repeated five times.

3. Results and Discussion

The performance of the three algorithms was compared based on average execution time and optimal solution value. Convergence curves of optimal and average solutions were plotted. Path diagrams were also drawn, labeling carbon emissions of nodes on the path.

The study demonstrated that all three algorithms could effectively optimize the path to minimize total carbon footprint. A simple test case with a 5-node graph was utilized for illustrative purposes. The starting point was node 0, and the endpoint was node 4, with the adjacency matrix presenting distance and carbon emissions between nodes. The final path search results are shown in Figure 3.

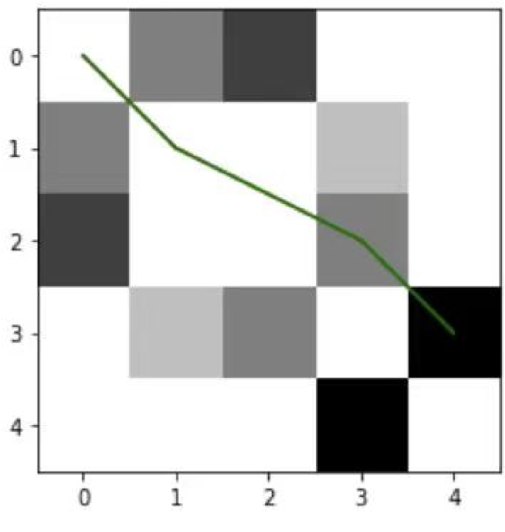

Figure 3. Map test data

It can be seen that in the process of simple map search, the SSA has the same effect as the genetic algorithm and particle swarm search in the direction of low-carbon optimization, and also finds the optimal path. Next, we compare the SSA with the other two algorithms in terms of convergence speed and optimal solution quality. The resulting data diagram is shown in Figure 4.

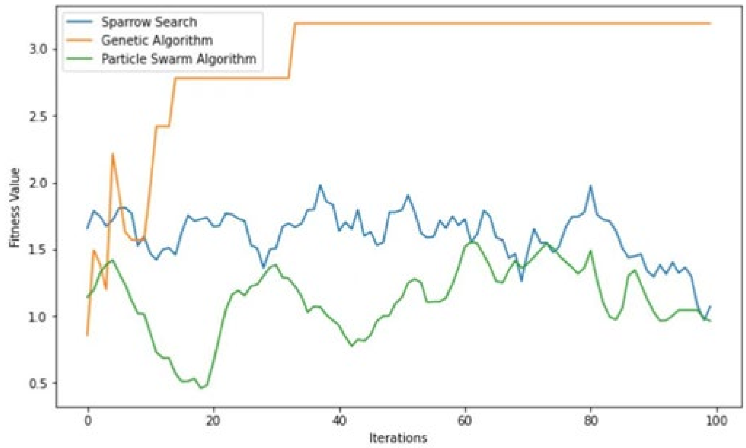

Figure 4. Data comparison line chart

Comparison of SSA with genetic algorithm and particle swarm algorithm. In order to see the change trend of the three algorithms more clearly, the first 10 values are listed, and the specific values of the three algorithms are shown in Table 1

Table 1. Examples of the first 10 columns of data

The first 10 data	SSA	GA	PSO
0	1.511452	1.170720	1.616402
1	1.624191	1.407757	1.447108
2	1.685499	1.434340	1.253959
3	1.766057	1.045726	1.020765
4	1.714610	1.040046	0.972844
5	1.689431	1.047073	0.985345
6	1.528291	0.994318	0.799700
7	1.612039	1.047073	0.627096
8	1.679940	1.047073	0.599657
9	1.805152	0.875399	0.600643
10	1.768021	0.894362	0.547724

On the chart, the advantages of the SSA can be reflected in the following aspects:

1. Convergence speed: It can be observed in the figure that the fitness value curve of the SSA decreases rapidly in the iterative process, indicating that the algorithm can quickly converge to a better solution. In contrast, the fitness curves of genetic algorithms and particle swarm algorithms may show more fluctuations or platforms and converge relatively slowly.

2. Optimal solution quality: It can be observed in the chart that the fitness value curve of the SSA can finally reach a lower value, indicating that the algorithm can find a better solution. In contrast, the fitness curves of genetic algorithms and particle swarm algorithms may stay at high values, indicating that the algorithms may fall into local optimal solutions.

5. Conclusion

In summary, the SSA demonstrates its advantages in cold chain logistics optimization through fast convergence speed and high-quality optimal solutions on graphs. Compared to Particle Swarm Optimization and Genetic Algorithms, it also exhibits strengths such as strong adaptability, fast convergence speed, and high-quality optimal solutions. The application of the SSA in cold chain logistics optimization and scheduling is also quite evident.

However, during the experimental process, we have also identified some drawbacks of the SSA:

Due to the interaction and complexity of the parameters, adjusting them can be challenging and requires a lot of time and effort. And if the initial solution quality of SSA is poor, the search results may be biased or the optimal solution cannot be obtained.

To address these shortcomings, we will further optimize the SSA in the future. We will combine it with other algorithms, such as the Golden Sinusoidal Algorithm and Curve Adaptive Weight, to enhance its capabilities. Additionally, we will optimize the algorithm to adapt to a broader range of application domains, not limited to cold chain logistics optimization and scheduling, enabling it to be used in various conditions and different application scenarios.

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